Impacts of novelty seeking on predictability in human mobility

Licia Amichi, Aline Viana Carneiro, Mark Crovella, and Antonio Loureiro

Abstract—Predicting how humans move within space and time is a central topic in many scientific domains such as epidemic propagation, urban planning, and ride-sharing. However, current studies neglect individuals’ preferences to explore and discover new places. Yet, neglecting novelty-seeking activities at first glance appears to be inconsequential on the ability to understand and predict individuals’ trajectories. In this work, we claim and show the opposite: exploration moments strongly impact mobility understanding and anticipation. We start by proposing a new approach to identifying moments of novelty-seeking. Based on that, we construct individuals’ mobility profiles using their exploration inclinations – Scouters (i.e., extreme explorers), Routiners (i.e., extreme returners), and Regulars (i.e., an individual with no extreme behavior). Finally, we evaluate the impacts of novelty-seeking, quality of the data, and the prediction task formulation on the theoretical and practical predictability extents. The results show the validity of our profiling and highlight the obstructive impacts of novelty-seeking activities on the predictability of human trajectories, in particular, on Scouters.

Index Terms—Individual Mobility, Exploration (Novelty-seeking), Mobility Profiling, Predictability, Prediction

I. INTRODUCTION

The understanding and modeling of human mobility became an accessible domain of study given the ubiquity of mobile devices, Internet connectivity, and positioning systems. The collection of large amounts of mobility data and individuals’ whereabouts urged scientists from diverse disciplines to examine the dynamics of human mobility behavior. In the literature, there are several representative models proposed to reproduce individuals’ trajectories and various robust predictors to forecast future locations. Indeed, accurate mobility models and predictors are crucial for epidemic prevention (e.g., the COVID-19 pandemics) [1], disaster response, and traffic management [2, 3]. Besides, such accuracies improve the services offered by pervasive computing applications [4], provide energy-efficient and cost-effective network infrastructures [5].

Previous studies [6, 7] showed that individual mobility is characterized by (i) high temporal and spatial regular patterns interrupted by (ii) irregular sporadic visits to unknown or rarely visited places. The pattern regularity is delineated by few visited locations, where users frequently return. On the other hand, irregularity and sporadic visits strongly impact predictability and are characterized as undetectable by predictors.

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Given the difficulties involved in anticipating location visits in mobility-related behavior, a frequent tacked question in the related literature is to what extent is human mobility predictable? In this regard, different predictive studies have been conducted, either to infer the theoretical upper bound (i.e., theoretical predictability) [2, 8, 9] or the prediction accuracy (practical predictability) [10–12]. Nevertheless, the empirical results suggest that the predictability takes variable values ranging from under 40% to higher than 90% [12]. Such varying results bring a new question: what are the origins behind these significant variations in the predictability measures? Alternatively stated, what are the essential factors that influence the predictability?

To answer this question, prior investigations demonstrated that the quality of the data considerably affects the predictability, namely the temporal and spatial resolutions [9, 12–14]. Indeed, human mobility is substantially more predictable when using finer-grained temporal resolution or when increasing the size of spatial units.

Another impacting factor is the prediction formulation. The literature reports a range of task formulations of the mobility prediction, namely, the next-cell, the next-place, the next-activity, or still the next-cell combined with contextual data. The most wide-spread versions are the next-cell and the next-place tasks, which formulations depend exclusively on the spatiotemporal specificity of the collected data. The other prediction formulations also require contextual information such as activity patterns, social ties, or semantic labels, making them less accessible and more challenging to analyze due to data acquisition and privacy concerns.

Withal, a non-negligible impacting factor, and focus of this paper, is the tendency of individuals to explore and discover new places. Admittedly, novelty-seeking is highly present in our daily lives, in fact, we are continuously hunting for new places and spots to go [12]. Moreover, the susceptibility to break the returning routine to explore and discover new places is heterogeneous among populations. In this vein, the literature reveals divergence in profiles according to the proclivity to explore [15, 16].

We claim that the high exploration susceptibility and related heterogeneous profiles of individuals indicate that the novelty-seeking factor is an essential element to consider and should not be overlooked, particularly for specific categories exhibiting high exploration activities. A resulting question is thus to what degree do novelty-seeking activities obstruct the predictability of human mobility trajectories?

In this paper, we answer this question. Toward this goal, we investigate the obstructive impacts of the novelty-seeking activities on the predictability extent of individuals’ mobility...
traces. In a preliminary version of this work [17], we profiled and evaluated the exploration phenomenon of individuals. Here, we build on this prior effort by presenting a much more comprehensive investigation and offerings:

- According to our investigations, we are the first to propose a novel per-user approach to distinguish between: (i) RV places visited for regular and routine activities, and (ii) EV places visited when being carried by the tendency to explore, and thus, exploit it to identify moments of novelty-seeking. In Section IV-B, we endorse our proposal by a thorough experimental validation and a performance comparison with a state-of-the-art approach.

- In Section IV-C, based upon the two captured types of locations, we split individuals’ visits into two categories: explorations and returns. Then, we define new profiling metrics that capture individuals’ propensity to explore new places and their intermittent behavior—i.e., the shift between the two types of visits. Subsequently, using the newly designed metrics we reveal the existence of three visiting profiles: *Scouters*, *Regulars*, and *Routiners*. For this, we use four urban datasets, describing people’s mobility from 5 cities in 3 different continents around the world (Section III).

- Finally, we are the first (to the best of our knowledge) to measure and quantify the impacts of novelty-seeking activities on the potential predictability of individuals’ traces and corroborate that exploration events are one of the main origins of the decrease in predictive performance. In addition to that, we also evaluate the effects of the most reviewed impacting factors on the predictability, namely, temporal and spatial resolutions and prediction formulation (Section V).

The remainder of this paper is organized as follows. We start with an overview of the related work in the field of predictability and its impacting factors in Section II. Following, in Section III we describe the datasets used throughout the study and the experimental settings. Next, in Section IV we present our profiling methodology. Afterward, in Section V, we excerpt the factor impacting the potential predictability of the mobility traces of each profile. Finally, we provide a discussion on the future research directions and open issues and challenges in Section VI.

Summary of the main outcomes: The similar cohesive groups resulting from the diverse and heterogeneous datasets suggest the generality of our profiling approach. Additionally, with the variation of the spatial and temporal resolutions and the prediction formulation, the different profiles are still plainly distinguishable and support the stability of our clustering. Essentially, understanding the impacts of novelty-seeking on predictability and prediction extents per-profile offers the opportunity to gain control by adjusting the predictors to the profiles. Namely, the profiling method helps identify who can be trusted and who is uncertain and requires further analysis. Withal, we show that although being the hardest to predict category, *Scouters* do have a routine, and their prediction is acceptable even in metropolitan-scale analysis, i.e., in urban areas where Points of Interest usually span a few square meters (for cells = 200 m): 80% of *Scouters* have more than 80% of prediction accuracy, what indicates a prediction error only in 20% of cases.

II. RELATED WORK

Over the last decade, human mobility was extensively scrutinized to understand the mechanisms ruling an individual’s movements. Several studies demonstrated that human movements are far from being random and have a high degree of predictability [18].

Song et al. [8] proposed, in their seminal work, an approach to measure the upper bound of its *maximum predictability* $\Pi^{\text{max}}$ based on the entropic level of a mobility trace. Analyzing a three-month-long CDR dataset of 50,000 users, their study revealed a 93% potential predictability in an individual’s mobility trace. Several subsequent studies tried to refine the predictability upper bound $\Pi^{\text{max}}$. For instance, Lu et al. [2] determined that in a CDR dataset containing the mobility trace of 2.9 million individuals, the upper limit of their predictability is estimated to be 85%.

Building upon the above findings, many advanced predicting algorithms were designed attempting to approach the theoretical predictability, such as Markovian predictors [10], Bayesian network models [11], neural network algorithms [19], or advanced deep learning approaches [20]. Lu et al. [10] sought to approach the theoretical limits of the predictability and utilized a Markov Chain based predictor with a varying order, and showed that the practical predictability (denoted by $s$ in this paper) reaches 91%. Moreover, they showed that higher-order Markov Chain models do not significantly improve the practical predictability. Gao et al. [11] implemented a novel predictor based on Bayes Networks and found that, using the Nokia Mobile Data Challenge that contains the mobility traces of 80 users, the practical predictability is about 50%.

Subsequent studies employed the same approach as in [8] tried to dig out the significant factors that affect the predictability of human mobility and shed light on the origins of the limitations in predicting the next location:

Spatial and temporal resolutions: Jensen et al. [13] examined the upper bound predictability using various types of mobile sensor data, namely, GSM, WLAN, Bluetooth, and acceleration of 48 days’ records for 14 individuals. Likewise, they reported high potential predictability for the data. Additionally, they showed that by varying the temporal resolution from a few minutes to a few hours, the highest predictive performance is obtained when the time scale is 4 to 5 minutes. Later, Lin et al. [9] used a high spatial and temporal resolution GPS dataset of 40 individuals. They showed that their finer-grained dataset produces higher upper bounds with predictability exceeding 98% with a temporal scale of 20 minutes or less. Likewise, Smith et al. [14] showed that the predictability is correlated with the temporal resolution and has an inverse correlation with the spatial resolution.

Type of prediction: Ikanovic et al. [21] emphasized the origins of the high potential predictability of individuals’ mobility obtained in earlier studies [2, 8]. They focused on
the next-place prediction that considers moments of transitions only, i.e., moving from a place to a distinct one, then estimated the upper bound limit of the predictability, and obtained significantly lower performance of approximately 71%. Thereby, they validated that the high estimated values of predictability in previous studies stem from the stationarity captured by the prediction formulation rather than movements. Similarly, Cuttone et al. [12] analyzed the predictability of a GPS dataset with the two widespread formulations of prediction, namely, the next-cell prediction and the next-place prediction. While the next-cell prediction shows to have a very high upper bound $\Pi_{\text{max}} = 95\%$ due to the stationarity in the human mobility, the next-place prediction appears to be more challenging with an upper bound lower than 68%.

**Novelty-seeking:** Recent studies showed the importance of considering individuals’ tendencies to explore and discover new locations when modeling their mobility [7]. Notably, Cuttone et al. [12] highlighted the importance of considering the exploration phenomenon when designing mobility predictors. Indeed, the higher an individual is prone to discover new places, the less predictable he/she is as it is impossible to forecast the unknown. This point led to an important question, *do all individuals explore at the same rate?* Or, *is there a category of individuals who explore more and hence are less predictable?*

In this regard, Pappalardo et al. [15] discerned two categories of people: explorers and returners. They based their classification on the number of regularly visited places: explorers visit many locations regularly, whereas returners limit their mobility between few places.

Besides, Scherrer et al. [16] using an unsupervised approach classified individuals into travelers and locals. Travelers have a spread mobility, whereas locals move in a more constrained area and revisit many of their locations.

We claim literature studies, although focusing on a very important mobility behavior, do not provide a precise understanding of individuals’ exploration tendency. Therefore, in our previous work [17], we proposed a mobility profiling based on individuals’ tendency to explore that we further improve in this paper. We revealed the existence of three main categories of individuals: (1) *Scouters or extreme explorers:* whose proclivity for novelty-seeking is the most eminent all over the week and have a more spread spatial mobility; (2) *Routiners or extreme returners:* who rarely perform explorations and have confined mobility; (3) *Regulars:* who have a medium behavior.

Accordingly, exploratory activities are not consistent among the population. While some groups depict a high propensity for discovering new areas and spots, others spend their time between familiar places. *Investigating how novelty-seeking inclinations of individuals affect the predictability of their mobility traces is a topic that has yet to be researched.*

**Position of our work:** While the impacts of prediction formulation and the quality of the data on predictability extents have been widely investigated, the limiting factors that arise from the intrinsic nature of human mobility have rarely been addressed. In this paper, on the one hand, we shed light on one of the main limiting factors of predictability, namely, individuals’ propensity to explore, and for the first time in literature, we present a newly-tailored method to recognize moments of novelty-seeking, and by the mean of this, we deeply improve our previously proposed mobility profiling [17]. On the other hand, we study predictability extents, which is the main focus of this paper, and evaluates how each of the prediction formulation, the quality of the data, and the proclivity for novelty-seeking influences the predictability.

### III. Data Description

In this work, we use two categories of data sources; three Global Positioning System (GPS) and one of Call Detail Records (CDR). These datasets capture spatio-temporal footprints of individuals’ mobility with high spatial and temporal resolutions. We outline our datasets in Table I and discuss them hereinafter.

#### A. GPS datasets

GPS technology allows tracking individuals’ movements with the highest level of accuracy and temporal frequency. We leverage three GPS data sources:

**Macaco:** it consists of anonymized digital activities tracks of 132 volunteers from 6 different countries collected in the context of the MACACO project [22]. For project-related privacy policies, this dataset is not publicly available. It provides a long-term and fine-grained sampling of individual behavior and network usage with a frequency of one sample every 5 minutes for a duration of 34 months. The data source contains about 900k tuples with raw GPS coordinates (latitude and longitude) and timestamps. Each tuple has a unique ID, which relates to a specific user.

**Privamov:** it contains mobility traces collected in the Privamov sensing campaign [23], capturing the spatio-temporal footprints of 100 unique volunteers over 15 months around a city in Europe. The data source was gathered over 156 million GPS records with a frequency of sampling roughly equal to a few seconds.

**Geolife:** the last GPS data source is the Geolife public dataset collected by Microsoft Research Asia [24–26]. The dataset stores information about the GPS trajectories of 182 individuals distributed in over 30 cities mainly in China, the USA, and Europe. The dataset includes time-stamped GPS tuples recorded every 1 to 5 seconds for more than 64 months.

#### B. CDR dataset

Mobile phone records consist of time-stamped and georeferenced records of voice phone calls and SMS of mobile network subscribers, called Call Detail Records (CDR). Each record usually contains the hashed identifiers of the caller, the timestamp for the call time, and the location of the cell tower to which the caller’s device is connected to when the phone activity is originated.

**ChinesedB:** this dataset is collected from 642K anonymized mobile phone subscribers in Shanghai, China 1, and contains

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1The collection was initiated by Shanghai University [27].
400k calls. It provides aggregated human footprints in the frequency of one location per hour during a period of 2 weeks. The locations in this dataset are gathered by merging the locations of the original CDR in each one-hour interval. Each location of an hour represents the user’s centroid of the hour with the precision of 200 meters according to the instruction of the data provider. This accuracy of positioning is higher than that of the original CDR.

### C. Data handling

Modeling and predicting individuals’ mobility focus on the location data i.e. latitude and longitude. First, we reconstruct the mobility trajectory $H_u$ of each individual $u$ by extracting the sequence of recorded locations along with the associated timestamps at fixed time periods $\delta$. $H_u = \langle (\text{lon}_0, \text{lat}_0, t_0), (\text{lon}_1, \text{lat}_1, t_1), \ldots, (\text{lon}_N, \text{lat}_N, t_N) \rangle$, with $t_i = t_0 + i \times \delta$.

Next, we discretize the geographical maps by placing uniform grids of $c$ meters $\times$ $c$ meters and draw out the grid cell IDs associated with the coordinates, by converting the tuple $(\text{lon}_i, \text{lat}_i)$ into a cell identifier $(id_i = \lfloor \frac{\text{lon}_i}{c} \rfloor, \lfloor \frac{\text{lat}_i}{c} \rfloor)$ as in [12], where $c$ meters is the cell-size in the grid. Hence, the mobility trajectory of the individual $u$ is converted into sequences of timestamped discrete symbols—a discrete mobility trajectory—$T_{u,c} = \langle (id_0, t_0), (id_1, t_1), \ldots, (id_N, t_N) \rangle$.

Afterward, given that the location of each individual is obtained at different uniform temporal rates in our GPS data sources i.e. 5 min for the Macaco, few seconds for Privamov, and 5 seconds for Geolife, we re-sampled all the GPS datasets to have an equal frequency of one sample every 5 min, i.e., $\delta = 5\text{min}$. However, some records can be missing due to delayed measurements produced by the sleeping phases of mobile devices collecting the data. Hence, to have a more uniform and complete traces, we comply with some steps proposed by Chen et al. [27] and complete them as follows

- First, per individual $u$, we identify the most frequent daily location $id_{wp,A}$ between 10 am and 11 am and name it workstation $A$.
- Second, we locate the most visited location $id_{wp,B}$ between 2 pm and 5 pm and name it workstation $B$.
- Next, we determine the most prevalent place $id_H$ between 2 am and 6 am (night), which we refer to as home.
- Once home ($id_H$), workstation $A$ ($id_{wp,A}$), and workstation $B$ ($id_{wp,B}$) locations are identified, we complete the mobility trajectory $T_{u,c}$ with a new record $(id_{wp,A}, t_x)$, where $t_x$ is the timestamp of the record.

- if a record is missing at $t_x \in [2\text{ pm}, 5\text{ pm}]$, we add the tuple $(id_{wp,B}, t_x)$ to the mobility trajectory $T_{u,c}$.
- if a record is missing at $t_x \in [2\text{ am}, 6\text{ am}]$, we add the mobility trajectory $T_{u,c}$ the record $(id_H, t_x)$.

### D. Experimental settings

In what follows, we give a brief description of the parameter settings we used in this study. Unlike in our previous works [17], we define a complete day for the GPS datasets as a day in which an individual has on average one record each 15 min. And select only participants that have at least 1 month of complete days of data. We are left with 266 users: 84 in Macaco, 77 in Privamov, and 105 in Geolife. For the CDR data, given the low frequency of sampling, we define a complete day as a day having on average one record every 2 hours and select only participants that have at least 14 days of complete data, we are left with 4860 individuals.

We discretize locations to grid cells of size $c = 200\text{m}$, with a frequency of 1 record each 5 min for the GPS datasets, and 1 record per hour for the CDR dataset. There are two reasons to consider these spatial and temporal resolutions. First, we focus on the discoveries of new places on a daily basis, for instance, going to a new restaurant or a new shop. Considering the imprecision and uncertainty of GPS systems, we claim a cells of size $200\text{m} \times 200\text{m}$ roughly corresponds to daily regions of interest and can still captures discovery moments. Second, the higher is the temporal resolution the better is the understanding of human movements. Nevertheless, there is a tradeoff between expanding the set of selected individuals and increasing the temporal resolution. Although corresponding to the highest sampling interval among the presented GPS datasets, a resolution of 5 min allows uniforming the frequency of sampling between the different sources while increasing the number of individuals and being reasonable for capturing most movements. Hence, having different datasets with the same resolutions allows us to test our methods’ effectiveness and validate our work extensively.

**GPS data aggregation:** due to the small number of individuals in GPS data sources and considering that these sources are of the same nature (i.e., with the same frequency of sampling and duration of analyses (1 month)), we proceed as the following. We aggregate the filtered and manipulated GPS datasets and label this new dataset as $Agg\_gps$. Starting from Section IV-E, we do not use the GPS datasets individually but employ the aggregated dataset $Agg\_gps$ to perform global characterizations and comparisons. In view of its different nature, the CDR dataset will be analyzed separately.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Category</th>
<th>Number of users</th>
<th>Duration</th>
<th>Frequency of sampling</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macaco [22]</td>
<td>GPS</td>
<td>132</td>
<td>34 months</td>
<td>5 min</td>
</tr>
<tr>
<td>Privamov [23]</td>
<td>GPS</td>
<td>100</td>
<td>15 months</td>
<td>few seconds</td>
</tr>
<tr>
<td>Geolife [24–26]</td>
<td>GPS</td>
<td>182</td>
<td>64 months</td>
<td>1 to 5 seconds</td>
</tr>
<tr>
<td>ChineseDB*</td>
<td>CDR</td>
<td>642K</td>
<td>2 weeks</td>
<td>1 hour</td>
</tr>
</tbody>
</table>

*The collection was initiated by Shanghai University [27].

**TABLE I:** Datasets description.
IV. PROFILING METHODOLOGY

Human beings’ movements are a mixture of repetitive and regular visits between known places and sporadic discoveries of new areas [6,15], both subject to a certain degree of uncertainty associated with free will and arbitrariness [6]. At each instant, an individual is confronted with an extensive list of choices concerning where and consequently, how to spend her time: she either returns to a place she visited in the past or explores a new location.

Contrary to the extensive literature investigations on mobility regularity patterns, we focus on the discoveries of new places. In particular, we intend to investigate whether there exist patterns when commuting from an exploration mode to a return mode and vice versa. For this, as in [7], we divide human movements into two primary states: explorations and returns. We define (1) the exploration as a discovery of a new location and (2) a return as a visit to a previously seen locality. Note that a central point in the exploration identification is to settle when a novelty-seeking moment happens. Hereafter, we describe our proposed strategy for this identification as well as our profiling methodology.

A. Formalization

Let $M$ be the Finite-State Automaton (FSA) describing an individual’s movements, as shown in Fig. 1, with two possible states: exploring ($E$) and returning ($R$). An individual $u$ can either be in the exploring state ($E$) or the returning state ($R$). Two possible transitions can affect an individual’s state: return ($T_r$ or $S_r$) by going back to historically known locations, and explore by discovering new spots ($T_e$ or $S_e$). In the exploring state $E$, discovering new areas ($S_e$) has no effect and keeps the individual in the state $E$. On the other hand, moving back to a known location ($T_r$), though recently explored, $M$ shifts the state from $E$ to $R$. In the returning $R$ state visits to usual places ($S_R$) does not change the state, however, a discovery of a new spot ($T_e$), shifts the state back to the $E$ state.

![Fig. 1: Finite-State Automaton $M$.](image)

B. Novelty-seeking identification

Strictly speaking, for an individual an exploration is the discovery of a new geographical location, i.e., a place where she was never seen before. Nonetheless, existing works tackling the exploration problem consider the first occurrence of a location in the mobility trace as an exploration [7,12], which leads to an overestimation of exploration events. This means that the first appearance of the home location or the workplace in the sequence is viewed as a moment of novelty-seeking. Yet, overvaluing the frequency of exploration events might twist the understanding of the exploration problem. Hence, given the mobility trace of an individual $u$, how can we distinguish her novelty-seeking visits from her routine visits?

We propose a newly tailored per-user approach to distinguish between locations used for exploration visits and familiar regularly visited locations, the approach is described in Algorithm 2. Besides, to verify and validate our approach we conduct a performance comparison with the state-of-the-art location classification algorithm proposed by Papandrea et al. [28] and described in Algorithm 1:

1) Baseline identification: we use the widespread framework proposed by Papandrea et al [28] as a baseline strategy. Grounds for their seminal per-user scheme that allows the evaluation of the importance of a place in a user’s daily mobility, meeting our case of study –i.e., individual mobility–. Moreover, it allows the classification of the locations according to their relevance from a single user viewpoint.

For each user $u$, we compute the Relevance $R_u(id_i)$ of each of her visited locations $id_i$ (cf. Algorithm 1, lines 4–5),

$$R_u(id_i) = \frac{d_{\text{visit}}(id_i,u)}{d_{\text{total}}(u)},$$

where $d_{\text{visit}}(id_i,u)$ is the number of days the individual $u$ visited the location $id_i$, and $d_{\text{total}}(u)$ is the number of days the individual has been active.

Following, as in [28] we use the $k$-mean unsupervised approach with 3 components to classify the locations into: (1) Mostly Visited Places (MVP), i.e., locations most frequently visited by the user; (2) Occasionally Visited Places (OVP), i.e., locations of interest for the user, but visited just occasionally; (3) Exceptionally Visited Places (EVP), i.e., rarely visited locations (cf. Algorithm 1, line 7).

Algorithm 1 Baseline identification

1: function location_classification_b ($T_u,c$)
2: $T_{\text{Relevance}}=T_{\text{MVP}}, T_{\text{OVP}}, T_{\text{EVP}} \leftarrow \emptyset$
3: $F_u \leftarrow \text{UNIQUE}(T_u,c)$
4: for $j \in F_u$ do
5: $T_{\text{Relevance}}[j] \leftarrow \text{COMPUTE_RELEVANCE}(j)$ $\triangleright$ (1)
6: end for
7: $T_{\text{MVP}}, T_{\text{OVP}}, T_{\text{EVP}} \leftarrow k$-means($T_{\text{Relevance}}$, 3)
8: return $T_{\text{MVP}}, T_{\text{OVP}}, T_{\text{EVP}}$
9: end function

2) Visitation-frequency-based identification: likewise, we propose a per-user method for the classification of the locations. Yet, unlike the baseline approach, we evaluate the importance of a location for a user $u$ according to the number of times she was seen in that location, i.e., the frequency of appearance of the location in her mobility trace.

Let $F_u = \{id_1, id_2, \ldots, id_n\}$ be the set of location visited by the user $u$ and consider Algorithm 2, which details the steps of this method. First, for each location $id_i \in F_u$, we assign a weight $w$ outlining the visiting importance of $id_i$ among the whole set of trajectory’s visited locations (cf. Algorithm 2, lines 4–5). It is given by,

$$w_u(id_i) = \frac{\text{freq}_u(id_i, T_{u,c})}{\sum_{j=1}^{n} \text{freq}_u(id_j, T_{u,c})},$$

where $\text{freq}_u(id_i, T_{u,c})$ is the frequency of appearance of location $id_i$ in the mobility trace of user $u$.
where \( f_{\text{freq}} \) is the number of occurrences of the location \( id_i \) in the discrete mobility trajectory \( T_{u,c} \) of the user \( u \). Next, we compute the average value of the visitation frequency \( \overline{w}_u = \frac{1}{|T|} \sum_{i=1}^{|T|} w_u(id_i) \), per-user \( u \) (cf. line 7).

Following, we categorize the visited locations into locations used for: (1) Exploratory Visits (EV), (2) Return Visits (RV). Each location \( id_i \) that has a weight \( w_u(id_i) \geq \overline{w}_u \times \text{level} \) is added to the set of locations used for RV, \( T_{RV} \) (cf. lines 9–10), otherwise it is assigned to the list of places used for EV, \( T_{EV} \) (cf. Algorithm 2, 11–12).

Algorithm 2 Visitation-frequency-based identification

1: function \( \text{location\_classification}\_\text{a} \) (\( T_{u,c} \), level)
2: \( w_u, T_{RV_u}, T_{EV_u} \leftarrow \emptyset \)
3: \( F_u \leftarrow \text{UNIQUE}(T_{u,c}) \)
4: for \( j \) in \( F_u \) do
5: \( w_u[j] \leftarrow \text{FREQUENCY}\_\text{OF}\_\text{APPEARANCE}(j, T_{u,c}) \)
6: end for
7: \( \overline{w}_u \leftarrow \text{MEAN}(w_u) \)
8: for \( j \) in \( F_u \) do
9: if \( w_u[j] \geq \overline{w}_u \times \text{level} \) then
10: \( T_{RV_u} \leftarrow \text{ADD}(j) \)
11: end if
12: \( T_{EV_u} \leftarrow \text{ADD}(j) \)
13: end if
14: return \( T_{RV_u}, T_{EV_u} \)
15: end function

The parameter level is critical and should be carefully tuned to allow a thorough capture of moments of novelty-seeking. Indeed, high values for level can induce an overestimation of explorations, while small values lead to a neglect of novelty-seeking moments. To quantify its impact, in Section IV-B, we evaluate the level parameter under two distinct values: level = 80%, corresponding to a less conservative identification (i.e., more explorations), and level = 20%, corresponding to a more conservative identification (i.e., more returns).

3) Level impact and baseline comparison: first, using the baseline identification approach (Algorithm 1), we categorize the visited places into EVP, OVP, and MVP. Next, we classify the visited locations into EV or RV using the proposed Algorithm 2 with level \( \in \{20, 80\}\)%. Finally, we measure the fraction of places within each category of places and evaluate their average visitation frequency, as shown in Figure 2.

Figure 2 (a) reports the percentages of places classified within each category extracted from our datasets; EVP, OVP, and MVP by Algorithms 1, EV and RV by Algorithm 2. First, we observe the high ratio of EVP jointly with OVP categorized by Algorithms 1, for all GPS datasets, more than 78% of the places, –i.e., EVP ∪ OVP– are not integrated into the daily routines of the individuals. Note that the CDR dataset describes visits in a smaller temporal resolution (i.e., per hour), this naturally impacts the precision in exploration inference of visits. Likewise, in all datasets, the proportion of locations used for EV surpasses 78% when level is set to 80%, and is higher than 50% with level = 20%. Moreover, we can notice in the case where level = 80%, the proportion of places classified as EV by Algorithm 2 corresponds roughly to the percentage of places categorized as EVP ∪ OVP by Algorithm 1. In contrast, in Algorithm 2 with level = 20% the fraction of places labeled EV is almost equal to the faction of locations classified as EVP by the baseline Algorithm 1.

Figure 2 (b) illustrates the proportion of the average frequency of visits towards each category of places. Firstly, we see the markedly high proportion of visits to locations used for RV, more than 90% of the visits are towards this category of places for level \( \in \{20, 80\}\)%.

In Table II, we report the percentage of intersection between EV places and EVP, then between EV and EVP ∪ OVP.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>EV (80%) ∈ EVP</th>
<th>EV (20%) ∈ EVP</th>
<th>EV (80%) ∈ EVP ∪ OVP</th>
<th>EV (20%) ∈ EVP ∪ OVP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Macaco</td>
<td>60.1%</td>
<td>47.71%</td>
<td>78.33%</td>
<td>68.38%</td>
</tr>
<tr>
<td>Privamov</td>
<td>50.75%</td>
<td>36.58%</td>
<td>76.92%</td>
<td>65.38%</td>
</tr>
<tr>
<td>Geolife</td>
<td>41.19%</td>
<td>33.76%</td>
<td>67.82%</td>
<td>59.18%</td>
</tr>
<tr>
<td>ChineseDB</td>
<td>88.78%</td>
<td>61.94%</td>
<td>98.27%</td>
<td>84.23%</td>
</tr>
</tbody>
</table>

Table II: Percentage of EV places present in \( T_{EV} \) and in \( T_{EV} \cup T_{OVP} \), with level \( \in \{20, 80\}\).
of an individual, we notice the significant overlap between the classifications of our proposed method and the baseline approach ones."

Thereby, from one side setting level to 80% allows EV capturing exceptionally and occasionally visited places as the baseline approach. From the other side, it allows capturing more precisely, the visits related to the individuals’ proclivity to explore (i.e., locations that are rarely frequent). We claim thus a novelty-seeking identification method should consider both quantity and visitation frequency aspects of per-category locations.

In summary, the proposed method, Algorithm 2 offers a satisfactory classification of the visited places. First, it allows the detection of a higher number of places used for exploration visits (EV), on the other hand, it guarantees that the visitation frequencies to these locations are lower compared to the RV as well as EVP of Algorithms 1. Second, the performance of Algorithm 2 with level = 80% allows the identification of a higher number of places used for EV, and hence enables a more precise detection of moments of exploration compared to the setting with level = 20%. Indeed, the first occurrence of a location in the set of a user’s EV locations is presumed to be a moment of exploration. In the remaining of the paper, we use Algorithm 2 and set level to 80%, which allows a more precise way to distinguish locations used for exploration.

C. Profiling rules

Initially, each user \( u \) has an empty set of known locations \( \mathcal{L}_u(0) = \emptyset \). Using Algorithm 2 with level = 80% for each user \( u \), we classify her visited locations into EV and RV. Subsequent, all locations classified as RV are added to the set of known locations \( \mathcal{L}_u \leftarrow T_{RV} \). Therefore, each occurrence of a location present in the set of known locations \( \mathcal{L}_u \) is a return, else it is an exploration. Note that after the discovery of a new place, this latter is added to \( \mathcal{L}_u \), i.e., its next occurrence in the mobility trace will be viewed as a return.

After dissecting human visits into explorations and returns, for each user \( u \) we first extract two sets:

- **Returning set** \( ret_u \): is a set containing the sets of consecutive returns, \( ret_u = \{r_0, r_1, \ldots, r_n\} \), where each \( r_i = \{id_0, id_1, \ldots, id_x\} \) is a set containing the ids of the cells where the user \( u \) performed successive returns.

- **Exploring set** \( exp_u \): is a set containing the sets of consecutive explorations, \( exp_u = \{e_0, e_1, \ldots, e_n\} \), where each \( e_i = \{id_0, id_1, \ldots, id_x\} \) contains the ids of the cells where the user \( u \) performed successive explorations.

Next, we assign to each individual \( u \) two values: (1) \( #E = \text{avg}(|e_i|), e_i \in exp_u \), the average number of her successive explorations – the average number of consecutive self-transitions she made in the E state, and (2) \( #R = \text{avg}(|r_i|), r_i \in ret_u \) the average number of successive returns – the self-transitions she made in the R state.

To characterize how individuals balance the trade-off between revisits of familiar locations and new-places discoveries, we define the following metrics that utterly capture the exploration habits of an individual. The first metric captures the shifting habits between the exploration and the return modes. The second metric captures the susceptibility of users to remain in their routine rather than explore new places.

**Definition 1 (Intermittency \( \mu \)).** is the sum of the average number of successive explorations \( #E \) and the average number of successive returns \( #R \), \( \mu = #R + #E \).

The intermittency measure reveals whether an individual is versatile or prefers to remain steady with respect to a category of location (i.e., return or exploration). Namely, it helps to recognize if a user is constantly fluctuating between visits to familiar places and discoveries of new spots or once she starts a discovery, she does is it repeatedly, before switching to revisits and vice versa.

**Definition 2 (Degree of return \( \alpha \)).** is the angle whose tangent is the ratio between the average number of successive returns \( R \) over the average number of successive explorations \( E \), \( \alpha = \arctg \left( \frac{#R}{#E} \right) \).

The degree of return describes the exploration conducts of an individual compared to her returns. Having a high degree of returns suggests that: the average number of successive returns is higher than the average number of successive explorations \( #R > #E \). Hence, the degree of return reveals what kind of explorer an individual is: whether she visits many new places on a row, or just after a few discoveries she goes back to a familiar location.

In what follows, we investigate whether the novelty-seeking habit is the same among the population or if it is a distinctive property. Namely, if there exist patterns followed by individuals while shifting between the exploration mode and returning mode or if there are several groups of users sharing the same habits but distinct from the others.

D. Mobility Profiling

After computing the intermittency \( \mu \) and degree of return \( \alpha \) for each individual, we use two clustering algorithms – the Gaussian Mixture probabilistic Model (GMM) and the \( k \)-means clustering method – to attest whether we can split the population into distinct cohesive and significant groups or not. To identify the best number of components of the clustering algorithms, and hence, the individuals’ types, we use the silhouette score statistical test and the Davies-Bouldin Index as well as we run one hundred fits for five different sets of clusters (two to six). Then, we consider the mean value when choosing the best score. The results show that the best performance is obtained with a clustering with three components (see Appendix ??).

We then apply the GMM and \( k \)-mean with three components on our data sources. We roughly obtain the same groups for both clustering algorithms. Thus, we only present the results obtained with the GMM algorithm. Fig. 3 depicts the normalized intermittency of individuals against their normalized degree of return and displays the clusters resulting from the application of the GMM algorithm on the GPS and CDR datasets. We can observe that our metrics can clearly capture the dissimilarity between the individuals in terms of human mobility dynamics. More importantly, the GMM
identifies three distinct groups that have identical intermittency and degree of return characteristics for all our data sources. We label the resulting groups as Scouters (red), Routiners (green), and Regulars (blue).

- Cluster 1: Scouters or extreme explorers, although holding varying degrees of return $\alpha$, they are remarkably lower compared to others’ scores. Moreover, they are notably intermittent — i.e., they are constantly shifting between the exploring and the returning states. These users are more prone to explore and discover new areas.
- Cluster 2: Routiners or extreme-returners have a surprisingly large degree of return. Besides, they tend to be steady in the different states of the automaton $M$ — i.e., they rarely break their routine. Hence, we can deduce that these users rarely explore and prefer to stick among their common and known places.
- Cluster 3: Regulars adopt a medium behavior and have large degrees of return compared to the Scouters. Though, their intermittencies are distinctly smaller than those of Routiners. These users constantly alternate between explorations and revisits. Yet, their proclivity to explore is less important than Scouters’.

![Graphs showing mobility profiling](image)

Fig. 3: Mobility Profiling.

The proposed approach captures two major mobility features that fully describe the exploration phenomenon, i.e., intermittency between returns and explorations, and the ratio of explorations compared to returns, and allows a natural clustering of the individuals.

### E. Profiles’ Mobility Traits

We now analyze the mobility behavior of individuals of each profile according to three dimensions: Relocation Activities, Temporal Activities, and Spatial Activities. To perform a global characterization we use the aggregated GPS dataset $Agg\_gps$ along with the ChineseDB data source.

The Relocation Activities features aim at quantifying and characterizing individuals’ visits, transition habits, and repetitiveness of visits. It involves four metrics:

- **Number of successive explorations**: it measures the average number of successive explorations performed by an individual.
- **Number of successive returns**: it estimates the average number of successive returns of an individual.
- **Number of stops**: it is the total number of distinct areas visited by an individual.
- **Visitation frequency**: it measures the frequency of visits to each area known by the individual.

The Temporal Activities features relate to the behavior of the individuals in time and captures the amount of time spent when discovering new places and when revisiting known locations. It comprises two measures:

- **Duration of successive explorations**: it is the average duration spent by the individual exploring.
- **Duration of successive returns**: it is the average duration spent by the individual revisiting known locations.

The Spatial Activities gives an intuition on the distances walked by the individuals when performing each type of visit. It consists in three features:

- **Total exploring distance**: it measures the total distance walked by the individual when exploring new places.
- **Total returning distance**: it is the total distance walked by the individual when returning to known places.
- **Radius of gyration $r_g$**: it estimates the total radius of gyration of the individual given by, \[
    r_g = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (r_i - r_0)^2} \]

In Table III we provide a finer view of the mobility traits of each profile and sustain our profiling method by highlighting the subsisting dissimilarity between the profiles. Due to the lack of space, we only give a short description of each profile. A more detailed characterization of the profiles and statistical results are provided in our previous works [17].

In summary, Scouters exhibit a high exploration activity and are characterized by markedly large sets of known places, which make them less regular in terms of spatial and temporal visits.

### V. REVEALING NOVELTY-SEEKING IMPACTS

In this Section, we aim to evaluate explorations’ effects (the first literature evaluation to the best of our knowledge) and the quality of the data on the two most widespread next location prediction next-cell and next-place tasks individually. We start by presenting the evaluation procedure followed in each prediction formulation. Following, we evaluate the performance reached in the next-cell formulation, and present the impacts of each of (1) the quality of the data and (2) the proclivity to explore. Finally, we examine the attainable accuracy of prediction in the next-place prediction task, and show the effects of the impacting factor in this case i.e., novelty-seeking.
A. Evaluation methodology

Hereafter, we describe the evaluation methodology to measure the impacts of each of the quality of data and individuals' tendency to explore on the two widespread prediction tasks. Note that the frequency of sampling for the $\text{Agg}_{gps}$ is set to 15 min, i.e., $\delta_{\text{Agg}_{gps}} = 15\text{min}$, and 1 h for the ChineseDB, i.e., $\delta_{\text{ChineseDB}} = 1\text{h}$, besides, we use a squared tessellation with cells of size $200 m \times 200 m$, i.e., $c = 200 m$.

1) Prediction tasks: there exist several ways to define the mobility prediction task depending on the quality of the available data and the objectives of the forecast. In this paper, we utilize the two most common prediction task formulations relying on location data only:

- **Next-cell**: given the mobility trace of an individual and considering a time window $\Delta t$, the next-cell prediction attempts to answer the subsequent question, *where will the individual go next?* The next-cell formulation is independent of the temporal dimension, it seeks to answer the following question, *where will the individual go next?* The next-place prediction aims at forecasting transitions between places. Hence, the triggering element is the transition of the user from her current location [12, 14].

2) Theoretical predictability: for each prediction formulation, we start by measuring the theoretical predictability of the mobility behavior of each of the Scouters, Regulars, and Routiners. This will provide insights about the capacity of correctly forecasting the mobility trajectories with an ideal and utter predictor. In this regard, we employ the state-of-the-art entropic-based approach proposed by Song et al. [8] to estimate the upper bound of the theoretical predictability $\Pi^{max}$.

For each user $u$ of each profile, given her discrete mobility trajectory $T_{u,c}$, we consider the stochastic sequence $x_{1}^{N} = \{x_{1}, \ldots, x_{N}\}$ where $x_{t}$ is the cell id of her location at time $t$. Then, we estimate the upper bound of the theoretical predictability $\Pi^{max}$ of the $x_{1}^{N}$ sequence as in [8].

3) Practical predictability: afterwards, we estimate the practical predictability of each of the Scouters, Regulars,
and Routiners. We compare the predictive performance of four predictors, namely, Markov Chain (MC) [29], Predicting by Partial Matching (PPM) [30], Sampled Pattern Matching (SPM) [31], and Active LeZi (ALZ) [32].

For the predictive performance comparison between the predictors, we measure the accuracy of the prediction achieved by each predictor. Given a stochastic sequence $x_1^N = \{x_1, \ldots, x_N\}$ of $N$ observations capturing the trajectory of an individual $u$. For each predictor and each user $u$, we initialize (i.e., "warm-up") the considered predictor using the $N_s = \frac{k}{2} \times N$ first elements $x_1^{N_s}$ (i.e., 20 days for the Agg_gps and 10 days for the ChineseDB). Second, we use the predictor to forecast the next location $x_{N_s+1}$. After this forecast, we update the predictor by considering $N_s \leftarrow N_s+1$ first elements of the stochastic sequence $x_1^{N_s}$. We then repeat the second step while $N_s \neq N$. Finally, when $N_s = N$, we stop the iterations and compute the success rate score $s_u$ for right predictions (accuracy of prediction) given by

$$s_u = \frac{1}{N - N_s} \sum_{t = N_s + 1}^{N} \mathbb{I}(x_t = x_t'|x_1^{t-1}),$$

where $x_t$ is the actual location and $x_t'$ is the predicted value.

**Experimental settings:** for the MC($k$) and PPM($k$) predictors, we choose a $k \in [1, 2]$. A $k$-th order MC predictor bases its forecast solely on the $k$ previous observations. Whereas, a $k$-th order PPM model employs a combination of MC($j$) models with $j \in [0, k]$ [30]. For the SPM($\alpha$), we choose $\alpha \in \{0.1, 0.9\}$. $\alpha$ represents the fraction of the maximal suffix employed to predict the future location. Note that the maximal suffix is the immediately longest foregoing set of locations whose copy appeared in the previous location history.

4) **Impacting factors:** finally, we evaluate the impacts of each of (1) the quality of the data and (2) individuals’ tendency to explore when relevant on the predictive performance achieved by each prediction task.

**Temporal variation procedure:** in the case of next-cell prediction, we investigate the effects of varying spatial and temporal resolutions on the accuracy of prediction $s$ for each mobility profile. Provided that the next-cell prediction task is independent of the temporal resolution, we do not investigate the impacts of the quality of the data factor on this formulation.

**Exploration-isolation procedure:** we identify moments of exploration using Algorithm 2 and remove them from the mobility trajectories or replace them and observe how they affect the predictors’ performances. These manipulations are performed for both prediction tasks but in different ways for the replacement procedures.

**B. Next-cell**

We first tackle the next-cell prediction task. We measure and analyze the theoretical and practical predictability of the mobility traces of individuals of each profile. Next, we investigate the effects of varying the spatial and the temporal resolutions on the accuracy of prediction. Finally, we identify moments of exploration and remove/replace them from/in the mobility trajectories, to probe the impacts of novelty-seeking on the predictive performance.

![Fig. 4: Distributions of the upper bound of the theoretical predictability $\Pi_{max}$ for individuals of each mobility profile.](image_url)

1) **Theoretical predictability:** Figure 4 portrays the distribution of the upper-bound predictability for each mobility profile for both the Agg_gps and the ChineseDB datasets. We can observe the high inherent predictability of the mobility trajectories of individuals of all profiles. Particularly, individuals of the Agg_gps have a more eminent degree of potential predictability principally due to the high frequency of sampling of the dataset $\delta_{Agg_gps} = 15\text{min}$, while $\delta_{ChineseDB}$ is set to 1 h. Admittedly, a higher frequency of sampling allows a more thorough capture of the stationarity and consequently, increases the degree of predictability [12]. More importantly, from Figure 4b, we note that the predictability $\Pi_{max}$ picks around 0.97 for the Routiners, 0.91 for the Regulars, and 0.87 for the Scouters. Taken together, these results indicate that Routiners are characterized by a very high degree of predictability while the Scouters are the least predictable individuals. Still, although presenting the lower predictability among the three mobility profiles, the Scouters' predictability is surprisingly high, mainly if considering the intuitive impossibility of predicting the uncertainties in Scouters mobility. Indeed, as reported in Table III, Scouters do have routines that consist in small sets of locations that they frequently visit.

2) **Practical predictability:** the estimations of the predictability upper bound of individuals’ trajectories reveals the high potential of predictability for all the profiles, with a lower score for Scouters (i.e., at most 0.87 in the ChineseDB dataset). Nevertheless, the prediction accuracy does not always reach the score provided by the theoretical measure [10] (see Section II). Hereafter, we evaluate the accuracy of prediction achieved by each of: MC, PPM, SPM, and ALZ.

In Figures 5 and 6 we plot the CDF of success score $s_u$ of the MC, PPM, SPM, and ALZ predictors with respect to their possible parameters $k \in \{1, 2\}$ for MC and PPM and $\alpha \in \{0.1, 0.9\}$. There is however little difference between the performance of the predictors. In the ChineseDB dataset, where we leverage a large number of users, for both of the Scouters and the Regulars, the best performances are achieved by the SPM models, whereas the lowest performances are achieved by the SPM particularly with $\alpha = 0.9$. For the Routiners, we observe that the performance of these predictors varies slightly with different settings. In general, the achieved performances by the distinct predictors are substantially comparable. Therefore, we employ the MC(1) for our subsequent analyses only.

For comparison simplification reasons, Figure 7 reports the distribution of the practical predictability of the MC(1) predictor for all of the Scouters, Regulars, and Routiners.
We can notice that the best performances are obtained with Routiners and the lowest ones with the Scouters. Emphasizing that the Scouters are the hardest to predict category of people, though they still present moments of regularity and thus, with high accurate prediction results (i.e., 80% of Scouters have an accuracy of prediction $s_u$ above 80%).

**Spatial resolution variation:** in Figures 8a and 8b, we investigate the correlation between the size of the geographical cells and the accuracy of prediction $s_u$ per mobility profile. For this purpose, we vary the size of the squared tessellations $c \in \{200, 400, 600, 800\}$ meters. Intuitively and according to previous studies [10] [12] the smaller are the locations, the less stationary behavior is ascertained in the mobility trajectories of the individuals, and hence, the less predictable they are.

Not surprisingly and in agreement with previous works, the accuracy of prediction improves substantially with the increase in the size of the geographical cells. This is observed with individuals of all the profiles without any distinction.

**Temporal resolution variation:** we now examine how the frequency of sampling affects the ability to predict the mobility trajectories of each profile. We reset the spatial resolution to $c = 200$ m, and vary the frequency of sampling

$$\delta_{\text{Agg}_\text{gps}} \in \{15, 30, 60\} \text{ minutes for the Agg}_\text{gps} \text{ dataset and } \delta_{\text{ChineseDB}} \in \{1, 2\} \text{ hours for the ChineseDB dataset.}$$

**Isolating explorations:** we want to scrutinize the impacts of novelty-seeking on the predictability of users’ trajectories. In the following, we reset the spatial resolution to $c = 200$ m and the temporal resolution to $\delta_{\text{Agg}_\text{gps}} = 15 \text{min}$ and
\[ \delta_{\text{ChineseDB}} = 1h \]. For each user \( u \) we use the proposed methodology presented in Algorithm 2 with level = 80\% to classify her locations into EV and RV. The places classified as RV are added to the set of known places \( \mathcal{L}_u \).

To evaluate the impacts of novelty-seeking on the accuracy of prediction \( s_u \) achieved by MC(1) we adopt three approaches:

- **1st proof-of-impact case:** we remove the novelty-seeking records for all profiles and measure the accuracy of prediction \( s_u \) achieved by MC(1) with the new sequences. Clearly, this removal decreases the size of the trajectories and consequently can increase the accuracy of prediction. The corresponding results are depicted in Figure 10.

- **2st proof-of-impact case:** as a first countermeasure to avoiding this size-related impact, we replace the novelty-seeking records with the last symbol met in the sequence. This action has the effect of adding a stationary period (equal to the size of each novelty-seeking period + 1). This approach is operated to assess whether the performance of the MC(1) predictor is only affected by the change in the length of the trajectories, or if the exploration events play a role. This substitution procedure is in favor of the predictor given that the stationary behavior is enhanced, the results are described in Figure 11.

- **3st proof-of-impact case:** as a second countermeasure to avoid both size-related impacts and stationarity increase, we identify moments of novelty-seeking and substitute them with a random symbol met in the sequence. This procedure allows tackling both size-related effects and attenuating stationarity betterment impacts. Figure 12 shows the obtained results.

The performance of MC(1) predictor indicates that, while the accuracy of prediction \( s_u \) is on average less than 60\% (resp. 90\%) for the least predictable class of users – i.e., Scouters – in the ChineseDB (resp. Agg-gps) dataset when considering novelty-seeking records (see Figure 7), Figure 10 shows that the predictor is considerably enhanced and can achieve an accuracy of prediction (on average) at least as high as 70\% (resp. 95\%) after removing exploration records. We have two hypotheses to explain this enhancement in the prediction accuracy: \( H_1 \): the more irregular visits are omitted from the discrete mobility trajectory \( T_u \) of a user \( u \), the more predictable she is. \( H_2 \): decreasing the lengths of a discrete mobility trajectory \( T \), allows the predictor to achieve better performance.

Replacing novelty-seeking records allows us to assess one of the origins of the betterments in the predictive performance of the MC(1) predictor. Figures 11a, and 11b show that when replacing novelty-seeking records by adding stationarity, the accuracy of prediction is in fact further improved compared to the removal approach. Whereas the replacement of novelty-seeking records with random locations does not necessarily improve the performance compared to the removal approach, it still achieves comparatively higher performances with regard to the original trace (see Figure 12). Particularly, Scouters who represent the most vulnerable category to the exploration phenomenon (their average prediction accuracy \( s_u \) is above 60\%),). These findings allow us to corroborate the harmful effects that exploration events have on the predictive performance of the classical MC predictor. Moreover, Scouters are more affected by these events as it could be seen within Figures 11 and 12, isolating these events engendered substantial improvements in the practical predictability of the Scouters compared to the other profiles.

**Summarizing remarks:** in a nutshell, in the next-cell prediction task individuals of all profiles are impacted by both the quality of the data and novelty-seeking. Increasing the temporal resolution of the data or enlarging the size of the spatial cells allows achieving higher accuracies of prediction \( s_u \). Moreover, although the high performances that are usually achieved with this prediction task mainly due to stationarity effects, moments of novelty-seeking do alter the predictive performance.
C. Next-place

We now tackle the next-place prediction formulation. We first reconstruct the discrete mobility trajectories $T_{u,c}$ of the individuals by removing stationarity records to fit the next-place prediction scenario. Next, we measure the theoretical $\Pi_{\max}$ and practical $s_u$ predictability of the discrete mobility trajectories $T_{u,c}$. After that, since this formulation of prediction is independent of the temporal resolution, we do not investigate the impacts of the quality of the data factor on this formulation of the prediction task. Finally, we measure the predictability of the three mobility profiles when removing and replacing moments of novelty-seeking.

1) Discrete mobility trajectories refurbishment: the next-place prediction formulation refers to the prediction of transitions between places. This formulation is more exposed to uncertainty as the stationarity behavior is omitted. Namely, the next-place prediction is about forecasting the next location where an individual is going to be and that should be different from her current one. Thereby, given the discrete mobility trajectory $T_{u,c} = \{ (id_0, t_0), (id_1, t_0 + \delta), \ldots, (id_N, t_0 + N\delta) \}$ of a user $u$, we identify consecutive tuples that have the same location $id$ and keep only the first tuple. Note that in this case the frequency of sampling $\delta$ is not constant and the size of the mobility trajectories is smaller.

2) Theoretical predictability: for each user $u$ of each profile, as in Section V-B, we estimate the upper bound of the theoretical predictability $\Pi_{\max}$ of the stochastic sequence $x^N = \{ x_1, \ldots, x_N \}$ extracted from her refurbished discrete mobility trajectory $T_{u,c}$.

Clearly, the accuracy of prediction $s_u$ is markedly lower than in the next-cell prediction task. In particular, the SPM performs poorly with the next-place prediction especially with Scouters. The remaining predictors have comparable performances, with an average accuracy around 10%, 24%, and 60% (25%, 26%, 34%) for Agg_gps (ChineseDB) dataset for Scouters, Regulars, and Routiners respectively. The achieved performances by the distinct predictors are substantially comparable. Therefore, to homogenize with the next-cell evaluation in what follows we use MC(1).

For comparison simplification, Figures 16a and 16b display the accuracy of prediction of the MC(1) predictor in the next-place prediction scenario in CDF curves, one for each mobility profile: Scouters, Regulars, and Routiners. We can observe that the MC(1) predictor fares poorly, notably with the Scouters, where 85% of them have an accuracy of prediction below 20% in the Agg_gps dataset and below 40% for the ChineseDB. This conveys that the uncertainty in a typical individual’s mobility trace is more significant than in the next-cell prediction.

Isolating explorations: we now analyze the impacts of exploration events on the next-place prediction formulation. We start by identifying moments of novelty-seeking per-user using the visitation frequency-based methodology Algorithm 2 with level = 80%. Next, we employ three methods to emphasize the impacts of novelty-seeking:

- 1st proof-of-impact case: as in the next-cell prediction analysis, we remove the novelty-seeking records (see Figure 17).
- 2nd proof-of-impact case: to avert size-related impacts, unlike in the previous prediction task we do not replace novelty-seeking records by adding stationary periods as it goes against the definition of the next-place formulation. Hence, given the last visited location $i$ if the current location $j$ is assumed to be an exploration we replace the novelty-seeking records $j$ with the most frequent location that usually appears after $i$. The results are depicted in Figure 18.
- 3rd proof-of-impact case: slightly different from the 3rd proof of impacts of the previous prediction formulation, we replace moments of novelty-seeking by a random symbol met in the sequence that is different from the last visited location. Figure 12 shows the obtained results.

Figures 17 displays the accuracy for the MC(1) predictor while keeping only familiar visits in the mobility traces. The accuracy of prediction is remarkably enhanced compared to the next-cell formulation case for all profiles notably for Scouters the average score is above 15% (above 50%) for the Agg_gps (ChineseDB).

The replacement of novelty-seeking places by the most probable known location allows a further enhancement of the performance in particular for Scouters (see Figure 18).

Further, we can discern the substantial harmful effects of exploration events on the predictability in the next-place prediction compared to the next-cell prediction. More importantly, the Figures show that Scouters are more impacted by the isolation of novelty-seeking records. The original median
Scouters is approximately less than 20% (see Figure 16), which is significantly lower than the performance of other profiles. Therefore, the removal or replacement of explorations events makes Scouters roughly as predictable as the other profiles.

Summarizing remarks: in summary, the next-place prediction task is a more challenging problem for individuals of all profiles. This formulation is more vulnerable to uncertainties as the stationarity behavior is overlooked. Therefore, the harmful effects of exploration activities are more discernible and have more impacts on the predictive performance.

VI. FINAL REMARKS AND OPEN ISSUES

Using real-world mobility traces, this paper proposes a new method for recognizing moments of novelty-seeking. Based on the exploratory tendencies of the population we revealed the existence of three groups of individuals with regard to their propensity to explore and discover new places, namely, Scouters (adventurous and prone to explore); (ii) Routiners, (steady and routinary), and (iii) Regulars (with medium behavior). This result has two major implications for the understanding of human mobility. First, in mobility modeling, individuals’ propensity to explore i.e., degree of return metric, as well
as the elapsed time before the occurrence of an exploration event i.e., intermittency metric are substantial concepts that should be further investigated, to assess the existence of new novelty-seeking related scaling laws per mobility profile, and hence provide more consistent and generative models able to reproduce human trajectories. Second, in mobility prediction the proposed profiling allows distinguishing hard to predict individuals due to their exploration activity from the rest of the population, and therefore propose more adequate predictors.

Furthermore, we took a fresh look at the most significant factors affecting the predictability extent of individuals’ mobility traces: (i) novelty-seeking, (ii) spatial and temporal resolutions, and (iii) prediction formulation. Utilizing our developed mobility profiling, we analyzed the effects of each factor on the predictability per profile. In accordance with previous studies, we showed that regardless of the mobility profiles, the next-cell prediction achieves higher degrees of practical and theoretical predictability compared to the next-place formulation. Particularly as a result, of the high stationarity presents in the next-cell prediction task. Besides, we asserted that increasing the size of the spatial cells leads to the increase of the stationarity and hence in the accuracy of prediction. Similarly, a finer-grained temporal resolution allows a higher capture of consecutive records with the same cell-id, and consequently a growth in stationary, which implies the achievement of higher prediction scores. More importantly, we shed light on the novelty-seeking phenomenon, as being a major factor impacting the predictability. Therefore, understanding the exploration phenomenon is fundamental to thoroughly model and predict human movements.

Meanwhile, further advances in understanding individual mobility are facing serious privacy issues. Indeed, human mobility trajectories containing geographical coordinates along with the date of collection are very sensitive data. Although the widespread of technological devices allowing the collection of individuals’ mobility traces, their acquisition is a nontrivial process and is getting more and more complex. Moreover, a large number of sensitive professional and personal information can be inferred solely through an individual’s mobility traces. Our future work can be divided into two directions: 1) investigate how our proposed mobility profiling can be adapted and used in a privacy-preserving environment. This means, given the mobility trace of a single individual, we aim at classifying her as a hard to predict individual or as a predictable one. 2) design a predictor that takes into account individuals’ inclination to explore and that will leverage the spatiotemporal analysis presented in a previous work to yield an intuition on the next area where an individual is prone to be in case of an exploration.

REFERENCES

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